Hybrid-Swarm Evolutionary Programming Based Technique for Optimal Placement and Sizing DGPV for Loss Control in Power System

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Abstract

Photovoltaic energy generation has significant development potential as a clean and renewable energy source. Non-optimum of distributed, grid-connected photovoltaic (DGPV) sizing and placement can lead to over-compensation or under-compensation in a loss reduction scheme. This study proposes a method for finding the optimal placement and size of DGPV to reduce total system losses in a power system. This work presents a new method of optimization that integrates Particle Swarm Optimization (PSO) and Evolutionary Programming (EP) in the Hybrid Swarm Evolutionary Programming (HSEP). This study purpose is to find the right placement and sizing of DGPV to control the loss in power system. DGPV were optimised utilising a metaheuristic algorithm with high exploitation capability. The proposed HSEP technique was utilized to optimize the sizing and location for DGPV for loss control in power system. This revealed that the proposed HSEP outperformed EP in achieving lower loss value.

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Introduction

Photovoltaic energy generation (DGPV) has increased rapidly in recent years. DGPV systems can be broadly classified into two groups based on their power generation methods.

First, centralised photovoltaic power station systems and the second is distributed photovoltaic systems household photovoltaic [1]-[2]. In comparison to previous generation methods, distributed generation encompasses a variety of configurations, and the resulting short-circuit current exhibits an unusual complexity as a result of these characteristics. DGPV is a term that refers to photovoltaic energy generation devices that are located in close proximity to the load. In comparison to centralised systems, it can minimise building costs and the cost of power producing systems [3].

As people have put a stronger value on environmental protection, energy conservation, and emission reduction, the utilisation of alternative energy sources becomes increasingly important [4]-[7]. As a result, some uncertain factors, such as the uncertainty of load and output power caused by the random charging and discharging behaviour of the plug-in electric vehicle, the uncertainty of wind turbine output power caused by random changes in wind speed, and the uncertainty of solar energy output power caused by random changes in solar irradiance, as well as the volatility of fuel prices and the randomness of load growth, will introduce risk [8]. Due to the fact that DGs are often connected to the distribution network, it is critical to consider the location and sizing of DG while building the power distribution system [9]-[13].

In this paper, the probability model construction and the selection of objective function in the process of location and capacity determination are studied. For this paper, a new method named Hybrid Swarm Evolutionary Programming (HSEP) is proposed for determining the optimal location and sizing to minimize power loss in the distribution system using IEEE reliability test system. Comparative studies have been conducted between the two techniques and revealed that the proposed HSEP technique is superior than the traditional EP.

Distributed Generation Technology

Distribution generation (DG) can be divided into four broad groups based on its ability to inject both actual and reactive electricity into the grid. Only active electricity is delivered by type 1 systems, such as photovoltaics and microturbines, and this power is injected into the main grid with the use of converters or inverters. Because of its use of synchronous machines, type 2 DG is capable of injecting both active and reactive power. In addition, type 3 DG only injects reactive power and operates at a power factor of zero, making it inefficient. And last but not least, type 4 is capable of infusing active power while simultaneously consuming reactive power [14]-[20]. It considers only DG type 1 will be installed into the transmission system for the transmission planning in terms of loss minimization. The IEEE 30-bus reliability test system is used as the test specimen for the purpose of validation process [15]. The power balanced equation when DG is installed, can be represented by: -

$$P_i = P_{DGi} - P_{Di} = -\frac{1}{A_{ii}} \sum_{\substack{j=i \\ j \neq i}}^{n} \left(A_{ij} P_j - B_{ij} Q_j \right) \quad (1)$$

Hence, it will become:

$$P_{DGi} = -\frac{1}{A_{ii}} \sum_{\substack{j=i \\ j \neq i}}^{n} \left(A_{ij} P_j - B_{ij} Q_j \right) \quad (2)$$

Optimization Techniques

This presents Evolutionary Programming (EP), Particle Swarm Optimization (PSO) and the proposed Hybrid Swarm Evolutionary Programming (HSEP).

A. Evolutionary Programming

Using EP, the DG's scale and location are initially generated as random numbers that should match the stipulated fitness equation. EP was inspired by the idea of evolution by natural selection. It emphasises the behavioural linkage between parents and their offspring. Depending on the situation, EP can impede or enhance fitness. EP involved several operators as the basic mechanics. The first step is initialization. Initialization routines use random number generators. Secondly, mutation is used to breed offspring from the original parents. Combination and selection are used to mix parents and the offspring populations; and ultimately find the survival of the fittest. The third step defines the combination rule. Finally, specify the selection rule [19],[21]-[22]. These steps will be repeated endlessly until the stop condition is fulfilled.

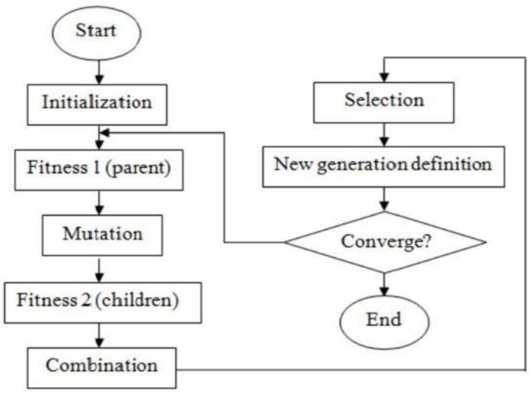


Figure1FundamentalEPProcess

The convergence of the difference between the highest and lowest fitness values serves as the function's stoppingcriterion. The flowchart for the EP is shown in the Figure 1 and Figure 2 below.

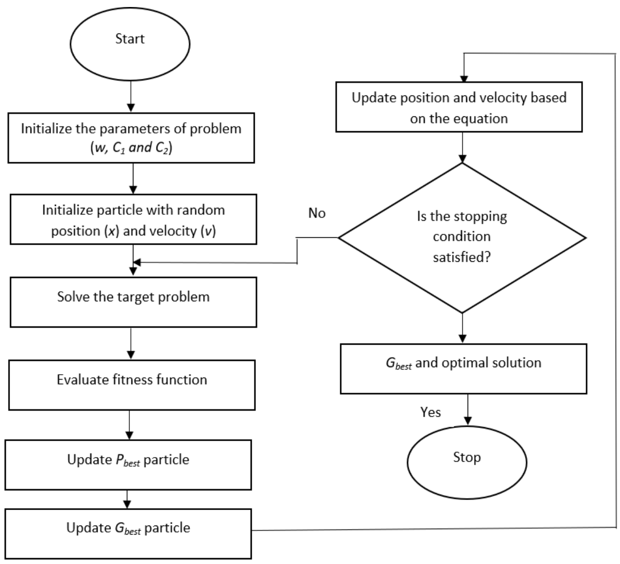


Figure2 EPFlowchart.

B. Particle Swarm Optimization

PSO was originally invented by Kennedy, Eberhart and Shiand was first intended for simulating social behaviour, as a stylized representation of the movement of organisms in a bird flock or fish school [23],[24].

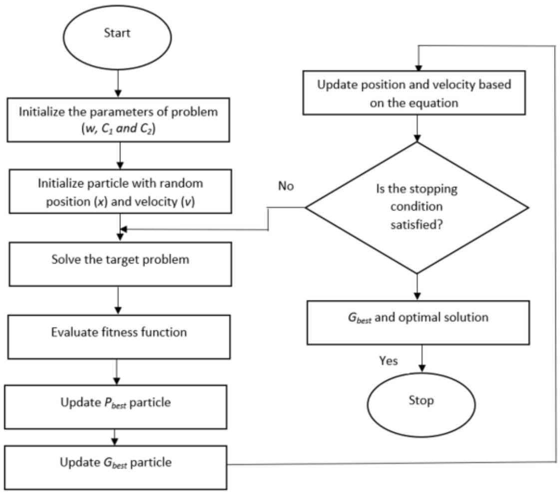


Figure3: Fundamental PSO Flow Chart.

Particles warm optimization (PSO) is an evolutionary computational technique used for optimization motivated by the social behaviour of individuals in large groups in nature. The variables in PSO can take any values based on their current position in the particle space and the corresponding velocity vector[23]. The flowchart for the PSO is shown in the Figure 3.In this study, PSO is used. Position of the individual particles are updated as in eqn. (3)[24, 25]:

$$V_{k+1}^{i} = V_{k}^{i} + c_1 r_1 \left(P_k^i - X_k^i\right) + c_2 r_2 \left(P_k^g - X_k^i\right) \quad (3)$$

where:

c_1, c_2 = cognitive and social parameters

r_1, r_2 =random numbers between 0 and 1

C. Hybrid Swarm Evolutionary Programming (HSEP)

By embedding Particle Swarm Optimization into Evolutionary Programming, this study presented a hybrid technique called Hybrid Swarm Evolutionary Programming (HSEP). The purpose of this work is to determine the new power loss (P_{loss}), the DG size 1 and DG size 2 (x1, x2), and the ideal position of DG1 and DG2. (loc1, loc2). The proposed HSEP technique was tested on the IEEE 30-bus RTS. The HSEP process can be presented in the following procedures:

The process begins with normal load flow to determine the power loss in the system before initialization takes place. Following that, the initialization process generates a population of twenty individuals subject to an inequality constraints which are actually the maximum and minimum bound of the DG sizes or locations. During initialization process, all the generated random individuals will give loss values lower than the loss obtained during the load flow process. With EP, the population is next subjected to Fitness 1 calculation. This is used to determine the fitness of each individual. For step-by-step debugging; the fitness value for each individual in the first iteration should be exactly similar with those in the initialization processes as this phase utilized the same individuals.

Once the fitness values have been calculated, mutation process begins. The mutation process is carried out using a modified PSO in this manner. Subsequently, second round of fitness calculation is performed using the off springs. Combination process is then conducted which combines the Fitness 1 and Fitness 2 populations. This process doubles the number if individuals. For instance, 20 individuals generated during initialization will become 40 individuals once combination process is done. The next process is the tournament process, or also known as selection. In this phase, 20 individuals will be identified to undergo the next iteration or evolution process. In general, there are several techniques can be implemented for this purpose. They are roulette wheel, pair wise comparison or elitism. In this study, elitism is adopted due to its simplicity. The stopping criterion is defined by evaluating the difference between the maximum and minimum fitness values. The optimal solution is achieved once the difference between the greatest and least fitness values is smaller than 0.0001. However, it also depends on the requirement of the optimization accuracy. The flowchart of the proposed HSEP is shown in Figure 4.

Figure 4 Proposed HSEP flowchart.

D. 30-bus Reliability Test System (RTS)

This study attemptstoidentify the optimal placement and sizing of the battery in distribution system. In this way, the battery is considered as DG Type 1. The objective function is loss minimization, implemented on the IEEE 30-Bus RTS using the proposed HSEP algorithm for optimal placement and sizing of DGPV. The initial value of real power loss was initially calculated using the normal load flow. This will be set as the constraint in such away that all the individuals generated during initialization will exhibit lower power losswhich will help to reach the minimal loss with the optimization process. It considers only DG type 1 which will be installed into the transmission system for the transmission planning for loss minimization scheme. The IEEE 30-Bus RTS is used as the test specimen for the purpose of validation process [20]. Figure 5 shows the IEEE 30-Bus RTS. This system is confined of 6 generator buses (including the swing bus) and 41 transmission lines; while other buses are the intermediate buses and load buses.

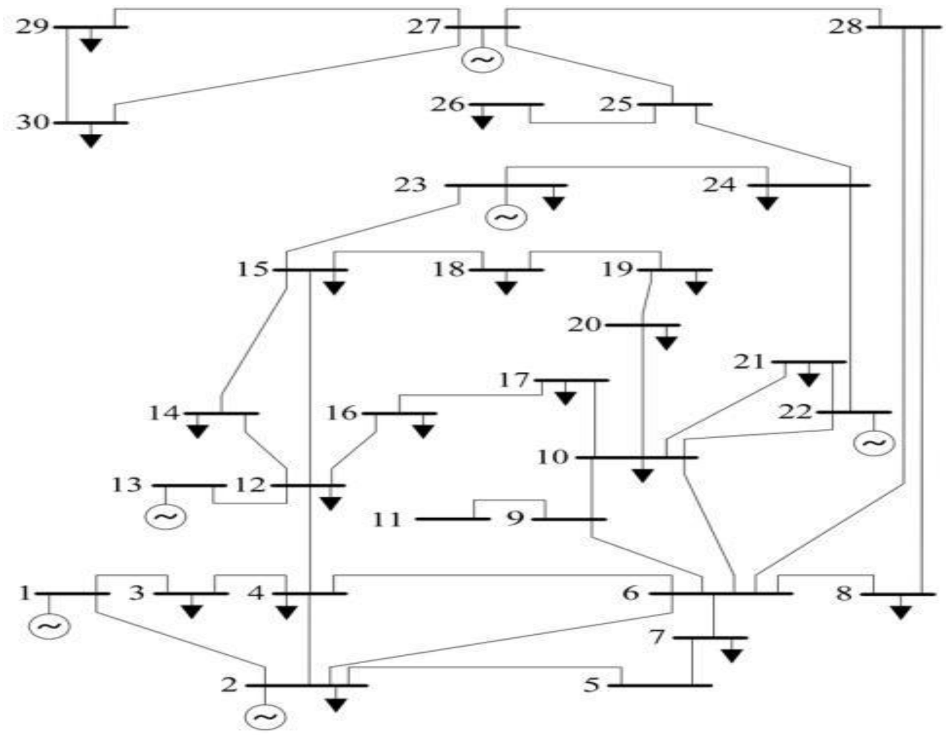


Figure5 IEEE30-BusReliabilityTestSystem(RTS).

Results and Discussion

The proposed HSEP optimization technique was conductedonthe IEEE30-busRTS with the objective tominimize the total transmission loss in the system. In this study, the sizing and location were identified using the proposed HSEP; which then compared with the traditional EP and PSO.The system was subjected to areactive power increase from 5MVAR to 20MVAR at Bus 25.Initialization results are also presented to show the randomness of the initial individuals. Subsequently, optimal results are also presented to show the performance of the proposed HSEP technique.

A. LoadingVariationSubjectedtoBus25

The system's reactive power load was varied gradually at 5MVar,10MVar,15MVar and20MVARat Bus 25 as tabulated in Table 1andTable2.Figure6,Figure7,Figure8andFigure9 tabulate the results during initialization confining sizing 1 (*x1*), sizing 2 (*x2*), location 1 (*loc1*),location2 (*loc2*) and power losses (P_{loss}).Figure 6, Figure 7, Figure 8 and Figure 9 depict the initialization results at load variations of 5 MVar,10MVar,15MVar and 20MVar.

At5MVarshown in Figure 6, the minimum power loss is 8.1368 MW.Thesizingfor sizing1(*x1*)is51.9175MWandsizing2(*x2*)is77.1944MWatbus15forlocation1(*loc1*)andbus21forl ocation2(*loc2*).At10MVar(Figure7),the minimumpowerloss is8.515MW.Thesizing at sizing 1 (*x1*) is 97.7238 MW and sizing 2(*x2*) is 44.4519 MW at bus 22 for location 1 (*loc1*)andbus28forlocation2(*loc2*).At15MVar(Figure8), the minimum power loss is 7.9627 MW. Thesizing at sizing 1 (*x1*) is 67.4525 MW and sizing 2(*x2*) is 73.7175 MW at bus 28 for location 1 (*loc1*)andbus22forlocation2(*loc2*).At20MVar(Figure9), the minimum power loss is 9.8234 MW. Thesizing at sizing 1 (*x1*) is 38.0608 MW and sizing 2(*x2*) is 88.3705 MW at bus 16 for location 1 (*loc1*)and bus21for location2(*loc2*). These values were generated during the initialization process. 20 individuals were initially generated which satisfied the equality and inequality constraints. These random values for each individual will reach to an optimal solution; where, only one value will be eventually identified once the solution is converged.

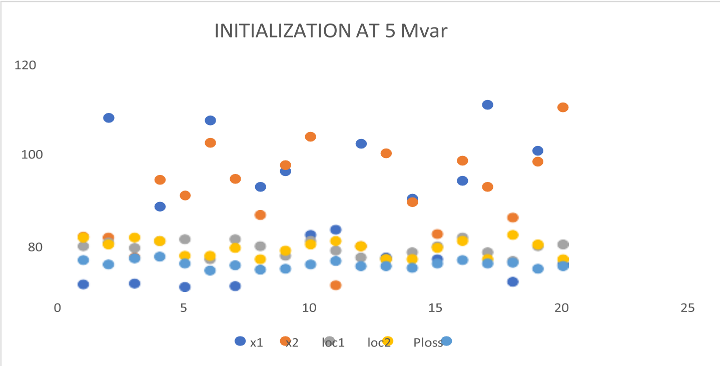


Figure 6: Initialization at Q_{d25}=5 MVAR

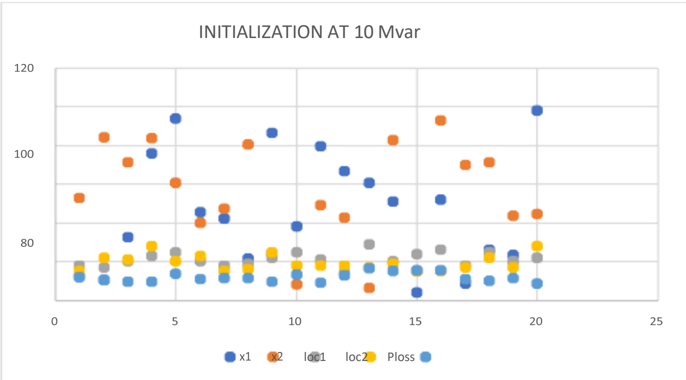


Figure 7: Initialization at Q_{d25}=10 MVAR

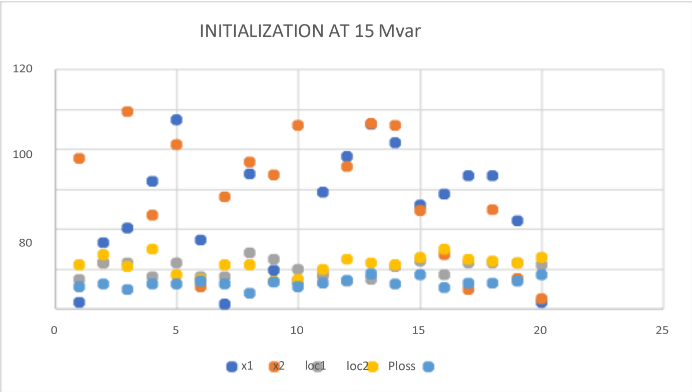


Figure 8: Initialization at Q_{d25}=15 MVAR

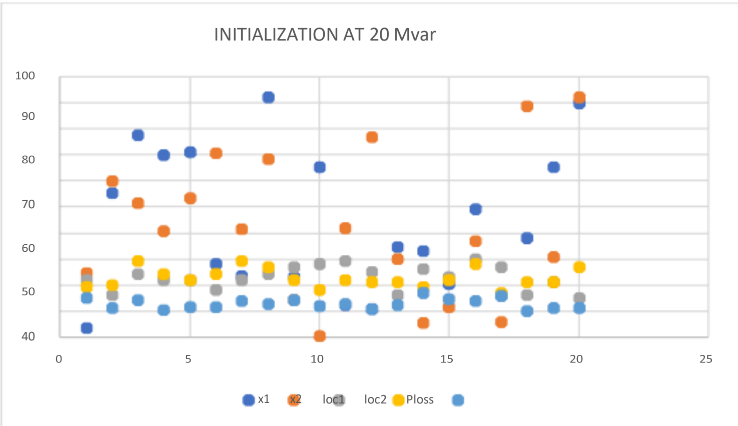
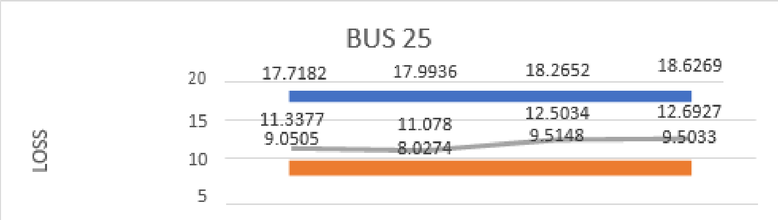


Figure 9: Initialization at Q_{d25}=20MVAR

Table 1 tabulatesthe results for power loss profile optimized inthree conditions which are the real power loss undernormal conditions, after EP optimization, and afterHSEP optimization. When the Q_{d25}value is subjected to 5Mvar, the result of power loss during pre-optimization is 17.7182MW.

Table1:Power LossResults for LoadVariation at Bus 25

	LOSS (MW)		
Qd 25 (MVAR)	Pre Optimization	Post Optimization (EP)	Post Optimization (HSEP)
5	17.7182	11.3377	9.0505
10	17.9936	11.078	8.0274
15	18.2652	12.5034	9.5148
20	18.6269	12.6927	9.5033



	5	10	15	20
Before EP (MW)	17.7182	17.9936	18.2652	18.6269
After HSEP(MW)	9.0505	8.0274	9.5148	9.5033
After EP(MW)	11.3377	11.078	12.5034	12.6927

Figure 10: Power loss profile caused for reactive powervariation at Bus 25

Optimization processes using EP resulted to loss reduction to11.3377 MW and its value is reduced to 9.0505 MW by using HSEP.When the $Q_{d25}$is increased to 10 MVAR the power loss duringpre-optimization is 17.9936 MW. EP managed to reduce its power loss to 11.078 MW, while the proposed HSEPtechnique managed to reduce the power loss to8.0274MW.On the other hand, whenthe$Q_{d25}$was subjected to15Mvar,theresultofthe power loss during pre-optimizationis18.2652 MW. Implementation of EP as the optimization technique managed to reduce the power loss to 12.5034 MW; while HSEP significantly reduced the power loss to9.5148 MW. For the case of Q_{d25} is adjusted to 20 Mvar, the result of power loss during pre-optimization is 18.6269 MW. EP reduced this value to 12.6927MW as the converged solution, while HSEP reduced it to 9.5033 MW. In all the load variations at Bus 25; the proposed HSEP technique outperformed EP.This implies that the proposed HSEP managed to exhibit outstanding performance over the traditional EP at all the reactive power load variation. Figure 10 illustrates its phenomenon. Apparently, the proposed HSEP technique shows lower profile as compared to the traditional EP; implying the superiority of the proposed HSEP.

Table 2: Optimal placement and Sizing UsingHSEPfor LoadVariations at Bus 25

	Location (Bus)		DGPV sizing (MW)	
Qd 25 (MVAR)	Loc 1	Loc 2	Size 1	Size 2
5	20	21	41.2499	86.0937
10	28	16	101.3377	55.3617
15	21	14	106.831	23.4166
20	17	15	91.38	70.6715

Table 2 tabulates the results for the optimal placement and sizingofDGPV for load variations at Bus 25. These results are tabulated separately for the purpose to present the locations and sizing for the optimal DGPV solved using the proposed HSEP.

When Q_{d25} is set to 5Mvar the optimal locations are Bus 20 for location 1 (*loc1*) and Bus 21 for location 2 (*loc2*).The corresponding DGPV size for sizing 1 (*x1*) is 41.2499MW and for the sizing2(*x2*) is 86.0937MW.WhenQ_{d25}issetto10Mvar, the optimal locations are Bus28 for location 1 (*loc1*) and Bus 16 for location 2(*loc2*). The DGPV size for sizing 1 (*x1*) is101.3377 MW and for the sizing 2 (*x2*) is 55.3617MW.WhenQ_{d25}issetto15Mvar, the optimal locations are Bus 21 for location 1 (*loc1*) and Bus14 for location 2 (*loc2*). This will require DGPV size forsizing1(*x1*) worth 106.831MW and for the sizing 2 (*x2*) is 23.4166 MW. When Q_{d25} is set to 20 Mvar the optimal placement is at Bus 17 for location 1 (*loc1*)and Bus 15 for location 2 (*loc2*). The corresponding DGPV size for sizing1(*x1*)is91.38MWandforthesizing2 (*x2*) is 70.6715MW. These results would be very beneficial to the power system utilities for their future planning action. These results could be given to the designers or vendors for the design purposes.

B. *Loading Variation Subjected to Bus29*

To extend the spectrum of this study, a second load bus, i.e. Bus 29 was subjected to reactive load variations. The system's reactive power load was varied to 5Mvar,10Mvar,15Mvar and20Mvar; implemented on the same IEEE 30-Bus RTS. The results during initialization processes for each load variation at Bus 29 are shown to show the randomness of individuals. The results are tabulated in Table 3and Table 4.Figure 11, Figure 12, Figure 13 and Figure 14 show the results of initialization process to show the values of sizing1(*x1*),sizing2(*x2*),location1(*loc1*),location2(*loc2*)andpower losses(P_{loss}). These results present the random locations and sizing for 20 individuals at each Q_{d29}reactive load variation.

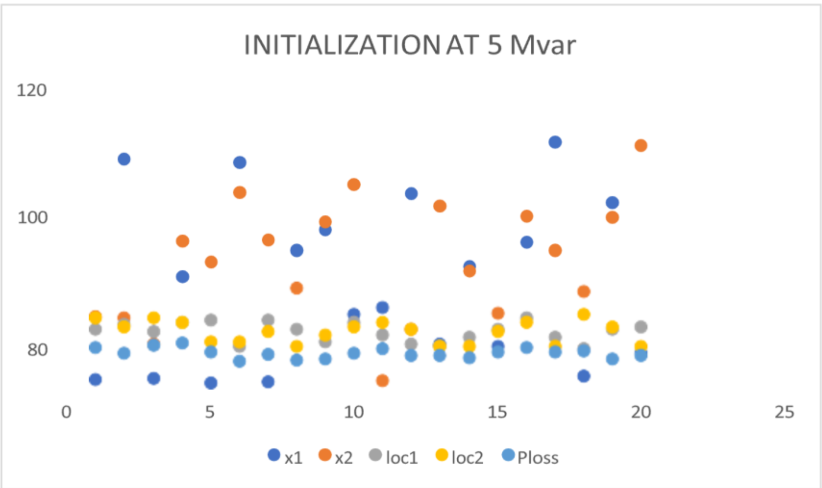


Figure 11: Initialization at Q_{d29}=5Mvar.

Figure 11, Figure 12, Figure 13 and Figure 14show the results for initialization process at load variations of5 MVar, 10 MVar, 15 MVar and 20 MVar. At 5MVar(Figure11),theminimumpowerlossis8.9701 MW. The sizing at sizing 1 (*x1*) is

90.3301MW and sizing 2 (*x2*) is 78.2992 MW at bus 15 forlocation1(*loc1*)andbus17forlocation2(*loc2*).At10 MVar (Figure 12), the minimum power loss is8.3831 MW. The sizing at sizing 1 (*x1*) is 84.1511MW and sizing 2 (*x2*) is 26.9317 MW at bus 28 forlocation1(*loc1*)andbus21forlocation2(*loc2*).At15 MVar (Figure 13), the minimum power loss is11.2264 MW. The sizing at sizing 1 (*x1*) is 55.6836MW and sizing 2 (*x2*) is 73.8997 MW at bus 28 forlocation1(*loc1*)andbus27forlocation2(*loc2*).At20 MVar (Figure 14), the minimum power loss is8.7814 MW. The sizing at sizing 1 (*x1*) is 72.9748MW and sizing 2 (*x2*) is 86.9264 MW at bus 28 forlocation 1 (*loc1*) and bus21 for location 2 (*loc2*). Apparently, all the individuals generated during initialization will result to P_{loss} value lower than the power loss calculated at the normal load flow, whereby the optimization processes using EP and HSEP have not been conducted yet. All random individuals will result to lower P_{loss}; set as the constraints during initialization.

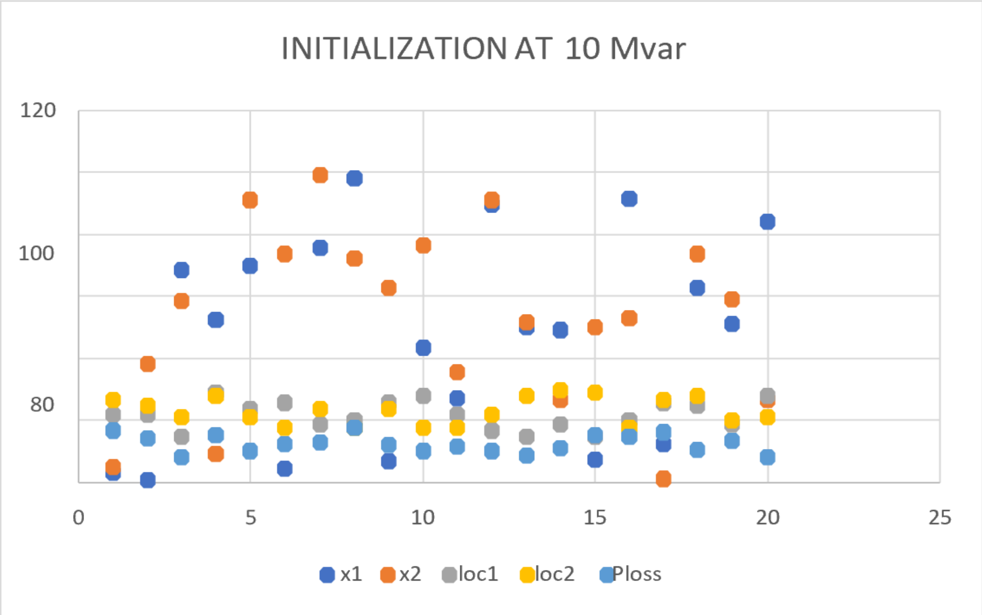


Figure 12: Initialization at Q_{d29}=10 Mvar.

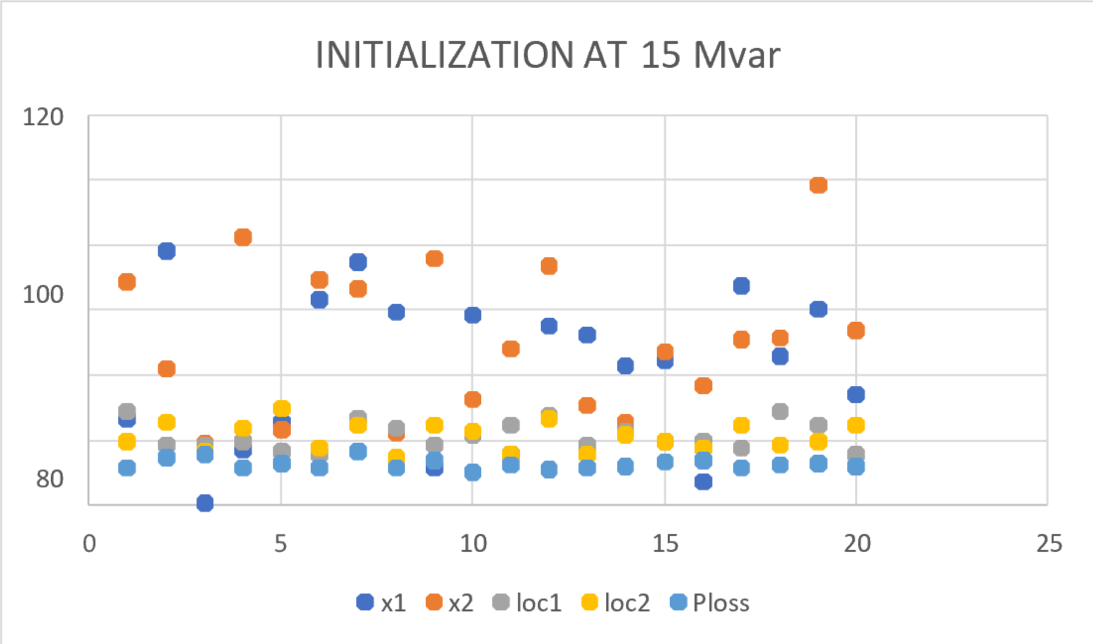


Figure 13: Initialization at Q_{d29}=15 Mvar.

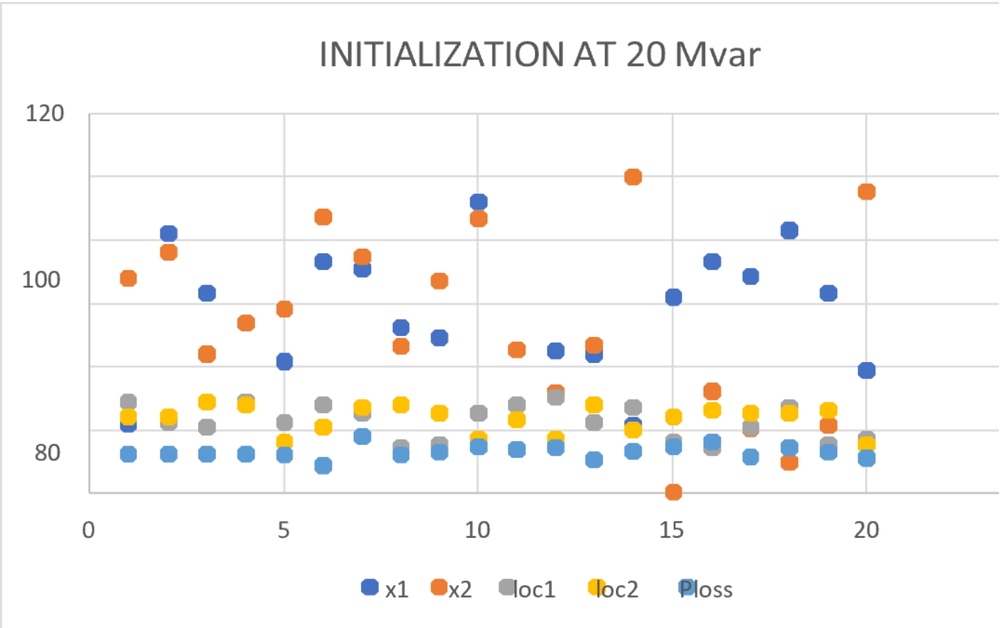


Figure 14: Initialization at Q_{d29}=20 Mvar.

Table 3 tabulates the results of power loss inthree conditions which are the real power loss undernormal conditions, after EP optimization, and afterHSEP optimization. When the Q_{d29} is subjected to 5Mvar, the result of power loss value during pre-optimization is 17.7284MW. The result of post optimization by using EP is10.9051 MW and by using HSEP it is 7.2804 MW.When Q_{d29} is adjusted at 10 Mvar the result ofpre optimization is 18.1164 MW. The result of postoptimization by using EP is 12.1714 MW and byusing HSEP it is 9.111 MW. This implies that the proposed HSEP managed to achieve lower power loss value as those solved using the traditional EP. It implies the superiority of HSEP.

When the Q_{d29} is adjustedto15Mvar,theresultofpower loss during pre-optimizationis18.6192 MW. EP managed to reduce its value to 13.7197 MW;while HSEP significantly reduced its loss value to 10.3284MW.This is a significant reduction and apparently HSEP outperformed EP. WhentheQ_{d29}isadjustedto20Mvar, the result of power loss during pre-optimization is 19.3855 MW. EP reduced it values to 13.8157MW while HSEP managed to achieve a much lower power loss to 9.3282 MW. This is again a significant reduction of power loss through optimization for DGPV installation in the transmission system. The proposed HSEP again outperformed the traditional EP in achieving a much lower loss value.

Table 3: Power Loss subjected using HSEP at Load Variation at Bus 29

	LOSS (MW)		
Qd 29 (MVAR)	Pre Optimization	Post Optimization (EP)	Post Optimization (HSEP)
5	17.7284	10.9051	7.2804
10	18.1164	12.1714	9.111
15	18.6192	13.7197	10.3284
20	19.3855	13.8157	9.3282

Table 4: Optimal placement and Sizing UsingHSEPat LoadVariations at Bus 29

	Location (Bus)		DGPV sizing (MW)	
Qd 29 (MVAR)	Loc 1	Loc 2	Size 1	Size 2
5	28	22	130.831	29.9843
10	17	15	94.1985	45.2562
15	19	17	51.0153	90.6364
20	28	21	145.4545	5.3365

Table 4 tabulates the results for the optimal placement and sizingofDGPVforloadvariationatBus29.WhenQ_{d29}issubjectedto 5 Mvar, the optimal locations solved using HSEP are Bus 28 forlocation 1 (*loc1*) and Bus 22 for location 2 (*loc2*).The corresponding DGPV size for sizing 1 (*x1*) is 130.831MWandsizing2(*x2*)is29.9843MW.WhenQ_{d29}issubjected to10Mvar,theoptimallocation isBus17 for location 1 (*loc1*) and Bus 15 for location 2(*loc2*). The DGPV size for sizing 1 (*x1*) is94.1985 MW and for the sizing 2 (*x2*) is 45.2562MW.WhenQ_{d29}isadjustedto15Mvar,theoptimallocation is Bus 19 for location 1 (*loc1*) and Bus17 for location 2 (*loc2*). This requires DGPV size forsizing1(*x1*)of51.0153MWandforthesizing2(*x2*) itis 90.6364 MW. When Q_{d29} is set to 20

Mvar, theoptimal locations are Bus 28 Bus 21. The optimal sizing for sizing 1 ($x1$) is 145.4545 MW and for sizing 2($x2$)it is 5.3365MW.

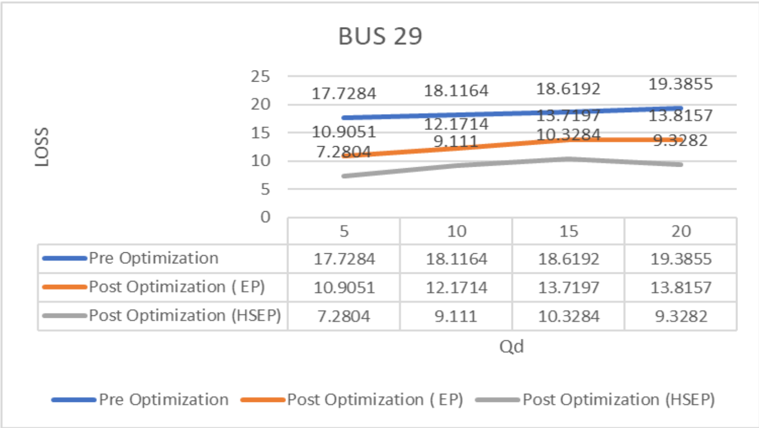


Figure 15: Power Loss caused by reactive powervariation at Bus 29

Figure 15 illustrates the profiles of power loss value for load variations from 5 Mvar to 20 Mvar subjected to Bus 29. In general, all the post-optimization profiles, solved using EP and HSEP are lowerthan those during the pre-optimization process; where load flow was running to calculate the power loss value at all the reactive load value.From the figure, HSEP exhibit lower power loss profile, indicating its superiority over the traditional EP.

Conclusion

This paper has presented Hybrid-Swarm Evolutionary Programming Based Technique for Optimal Placement and Sizing DGPV for Loss Control in Power System (HSEP). Optimal placement and sizing DGPV for losscontrol in power system are addressed in this studyusing HSEP, and compared with the traditional EP. When theHSEP algorithm is implemented on the IEEE 30-BusRTS, the result of powerlossis much better than EP, in terms of achieving lower power loss value at all reactive power loading.Various reactive loading conditionswere subjected to Bus25andBus 29.It implies that the proposed HSEP is consistently superior than the traditional EP. The developed optimization engine in HSEP could be conducted to solve other optimization problems in power system with minor modification or even to be tested on a larger test model.

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